Preliminary feasibility analysis of inner speech as a control paradigm for brain-computer interfaces

Nicolás Nieto[1,2,*], Hugo L. Rufiner[1] and Ruben Spies[2]

[1] Instituto de Investigación en Señales, Sistemas e Inteligencia Computacional, sinc(i), UNL-CONICET
[2] Instituto de Matemática Aplicada del Litoral, IMAL, UNL-CONICET.
*nnieto@sinc.unl.edu.ar

Abstract. Brain Computer Interfaces (BCIs) are useful devices that provide new ways of communication to people who have lost the capability of interacting with their environment. Although several paradigms have resulted in large improvements in the construction of BCIs, quite often they require great efforts from the patient or they are not able to generate natural and efficient interfaces. In that scenario, inner speech appears as a promising paradigm for tackling those problems. Nevertheless, the lack of publicly available databases largely precludes the analysis and development of methods for using this paradigm. In this work we use a recently released database to show that it is possible to classify and differentiate inner speech signals from signals acquired within other two well known paradigms. This is undoubtedly a first step in the search and construction of an inner speech based BCI.

Keywords: Electroencephalography · Machine Learning · Brain Pattern Recognition · Extreme Learning Machines

1 Introduction

Spinal injuries, strokes, cerebral palsy, amyotrophic lateral sclerosis, among other diseases, can interrupt the normal pathways that the brain uses for muscle control. For such patients, Brain Computer Interfaces (BCIs) provide an alternative way of interaction with the environment, offering great benefits [28,12]. In a BCI, the brain activity is usually measured by surface electroencephalography (EEG), as it is a standard and noninvasive technique [21]. EEG provides signals with good time resolution but with a poor spatial resolution and low signal-to-noise ratio. Once the signals are obtained, they are typically classified by machine learning techniques. These classifiers use the EEG signals to generate outputs for controlling external devices (wheelchairs, computers, etc.)

The so called "inner speech" paradigm has been studied using EEG [3,8,26], electrocorticography [24], functional magnetic resonance imaging and positron emission tomography scan [10,25,11,20]. The potential advantages of using inner speech as a control paradigm are clear, as it can generate more natural interfaces, allowing patients to execute an order, literally by just thinking about it. Nevertheless, compared to other paradigms, inner speech involves more complex neural networks of different cortical areas engaged in phonological and semantic analysis, speech production and other processes [24,16,1].

Although the understanding of inner speech has largely increased in the last few years, there is still not enough evidence to support the conjecture that this paradigm can in fact be used for efficiently controlling a BCI. The aim of this work is to show that it is possible to classify and differentiate inner speech signals from those acquired within other two well known paradigms. This is undoubtedly a first step in the search and construction of an inner speech-based BCI.

2 Materials and Methods

2.1 Data description

Tasks and participants. For the experiments, the dataset presented in [23] was used. This dataset contains EEG signals from ten healthy participants, all right-handed and native Spanish speakers. The participants were requested to perform three different conditions (paradigms): pronounced speech, inner speech and visualized condition. The data were acquired with a BioSemi ActiveTwo acquisition system of 128+8 channels at 1024 Hz. The number of trials varied among subjects. A more detailed description of the acquisition procedures and the number of trials for each subject can be found in [23].

EEG processing. In [23], the data were filtered between 0.5 and 100 Hz, and a notch filter was applied at 50 Hz. An Independent Component Analysis was applied in order to detect and remove noisy components, mainly contaminated with ocular and muscular artifacts. Finally, the continuous recording were split in 2.5 seconds trials. In this work, only the final two seconds of each trial were used to avoid possible evoked potentials produced by the stimulation protocol.

A similar approach to the Filter Bank Common Spatial Pattern (FBCSP) proposed in [2] was used for generating the spectral and spatial features. The band-pass filter frequencies used, in Hz, were: $[0.5, 4.0]$, $[4.0, 8.0]$, $[8.0, 12.0]$, $[12.0, 20.0]$, $[20.0, 30.0]$ and $[30.0, 45.0]$. From each band, a Common Spatial Pattern filter was learned and the average power in the first six spatial components were calculated. These six features for each one of the six bands generated the 36-dimensional feature vector used for classification. Finally, each feature was scaled between 0 and 1. A twenty-fold cross-validation was used, splitting the data in 80% and 20% for training and testing, respectively, for each subject.

2.2 Classification algorithm

Extreme Learning Machines. Extreme Learning Machines (ELMs) are single hidden layer neural networks, originally proposed in [15,14,13]. ELMs have been widely used in EEG signals classification problems [6,5,19,7,29,18,27,17]. The training process of an ELM consists of two steps. First, the matrix of input weights W and the vector of bias weights b are randomly set as independent realizations, usually of a uniform distribution. The second step consists of finding an appropriate output weight β. This is done by means of the Moore-Penrose generalized inverse [9]. One of the most appealing aspects of the ELMs is that they only have one hyperparameter that must be calibrated: the number of hidden nodes M. In this work, we use the regularized version of ELM formulated in [4], setting the regularization parameter $\lambda = 1$. The regularized ELM does not suffer from overfitting, which commonly appears when the number of hidden nodes is close to the number of training examples.

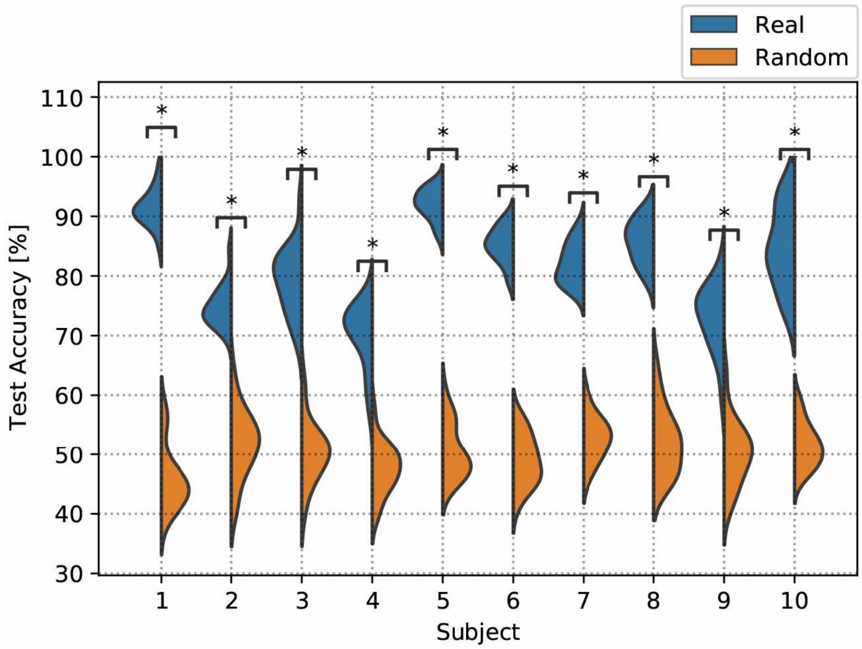

Fig. 1. Violin plots for the first experiment. Test accuracy distribution obtained with real and random labels, for each subject. Statistical significance according to Mann–Whitney-Wilcoxon test is marked with " * " ($p \leq 0.001$).

Relevance-Based Pruning. ELMs usually contain nodes that ought to be pruned out from the network in order to improve classification accuracy and to generate a more compact network. Here, the Relevance-Based Pruning (RBP) method proposed in [22] was used, as it gets rid of the need for computational expensive retraining while searching for the optimal number of neurons.

For finding the hyperparameter M, a three-fold cross-validation was performed within the training set, splitting the training data in 80% and 20% for train and validation subsets, respectively. In each fold, ten different random initializations of the parameter vectors W and b were generated. For each initialization in each validation fold, a grid search between 1000 and 50, with decremental steps of 50 nodes, was used to find the minimum number of nodes that maximizes the validation accuracy. Then, M was set as the average of the best number of hidden nodes obtained in each search. Once the appropriate number of nodes was obtained, the FBCSP and the ELM were trained over the whole training set and the testing accuracy was computed for each fold.

Finally, the same experiment was performed randomizing the condition label of the trials, allowing the comparison of the accuracy distribution obtained with the real and the randomized labels.

3 Results

In the first experiment, all the available trials in the inner speech and the visualized conditions were used, for each subject. The distribution of the test accuracy

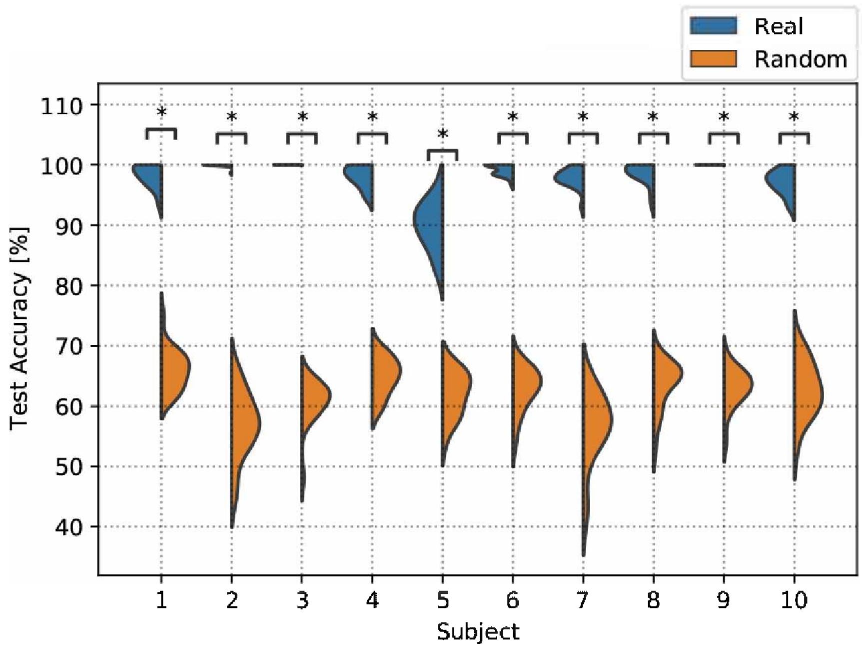

Fig. 2. Violin plots for the second experiment. Test accuracy distribution obtained with real and random labels, for each subject Statistical significance according to Mann–Whitney-Wilcoxon test is marked with “ * ” ($p \leq 0.001$).

with the real and the randomized labels for the 20 folds is shown in Figure 1. A Mann–Whitney–Wilcoxon two-sided test was performed between the accuracy obtained with each kind of label. The significance level was set to 0.001 and, for all subjects, significant differences were found.

For the second experiment, the inner speech and the pronounced speech trials were used. The distribution of the test accuracy with the real and the randomized labels for the 20 folds is shown in Figure 2. The same statistical test was performed and significant differences were found for all subjects. Moreover, the accuracy obtained in this experiment is consistently higher than the one obtained in the first experiment.

4 Conclusions

In an effort to substantiate the feasibility of an inner speech-based BCI, a comparison between conditions was made, showing encouraging results. This comparison allows us to state beyond any reasonable doubt that inner speech is clearly distinguishable from the other two examined conditions. Moreover, the brain mechanisms that generate each condition can be recognized by means of the EEG signal analysis. This can be thought of as a first milestone in the continuous working efforts for the construction of a more natural BCI. Needless to say, much further work has to be done to separate different classes within each condition. To encourage reproducible science, the code used in this work is publicly available at `https://github.com/N-Nieto/Feasibility_Analysis_Inner_Speech`.

References

1. Alderson-Day, B., Fernyhough, C.: Inner speech: development, cognitive functions, phenomenology, and neurobiology. Psychological Bulletin **141**(5), 931 (2015)
2. Ang, K.K., Chin, Z.Y., Zhang, H., Guan, C.: Filter bank common spatial pattern (FBCSP) in brain-computer interface. In: 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence). pp. 2390–2397. IEEE (2008)
3. Deng, S., Srinivasan, R., Lappas, T., D'Zmura, M.: EEG classification of imagined syllable rhythm using Hilbert spectrum methods. Journal of Neural Engineering **7**(4), 046006 (2010)
4. Deng, W., Zheng, Q., Chen, L.: Regularized extreme learning machine. In: 2009 IEEE symposium on computational intelligence and data mining. pp. 389–395. IEEE (2009)
5. Ding, S., Guo, L., Hou, Y.: Extreme learning machine with kernel model based on deep learning. Neural Computing and Applications **28**(8), 1975–1984 (2017)
6. Ding, S., Zhang, N., Xu, X., Guo, L., Zhang, J.: Deep extreme learning machine and its application in EEG classification. Mathematical Problems in Engineering **2015** (2015)
7. Duan, L., Bao, M., Miao, J., Xu, Y., Chen, J.: Classification based on multilayer extreme learning machine for motor imagery task from EEG signals. Procedia Computer Science **88**, 176–184 (2016)
8. D'Zmura, M., Deng, S., Lappas, T., Thorpe, S., Srinivasan, R.: Toward EEG sensing of imagined speech. In: International Conference on Human-Computer Interaction. pp. 40–48. Springer (2009)
9. Engl, H., Hanke, M., Neubauer., A.: Regularization of inverse problems. Mathematics and its Applications (Dordrecht) **375** (1996)
10. Fiez, J.A., Petersen, S.E.: Neuroimaging studies of word reading. Proceedings of the National Academy of Sciences **95**(3), 914–921 (1998)
11. Hickok, G., Poeppel, D.: The cortical organization of speech processing. Nature Reviews Neuroscience **8**(5), 393–402 (2007)
12. Holz, E.M., Botrel, L., Kaufmann, T., Kübler, A.: Long-term independent brain-computer interface home use improves quality of life of a patient in the locked-in state: a case study. Archives of Physical Medicine and Rehabilitation **96**(3), S16–S26 (2015)
13. Huang, G.B., Wang, D.H., Lan, Y.: Extreme learning machines: a survey. International Journal of Machine Learning and Cybernetics **2**(2), 107–122 (2011)
14. Huang, G.B., Zhu, Q.Y., Siew, C.K.: Extreme learning machine: theory and applications. Neurocomputing **70**(1-3), 489–501 (2006)
15. Huang, G.B., Zhu, Q.Y., Siew, C.K., et al.: Extreme learning machine: a new learning scheme of feedforward neural networks. Neural Networks **2**, 985–990 (2004)
16. Indefrey, P., Levelt, W.J.: The spatial and temporal signatures of word production components. Cognition **92**(1-2), 101–144 (2004)
17. Jin, Z., Zhou, G., Gao, D., Zhang, Y.: EEG classification using sparse Bayesian extreme learning machine for brain–computer interface. Neural Computing and Applications **32**(11), 6601–6609 (2020)
18. Kong, W., Guo, S., Long, Y., Peng, Y., Zeng, H., Zhang, X., Zhang, J.: Weighted extreme learning machine for P300 detection with application to brain computer interface. Journal of Ambient Intelligence and Humanized Computing pp. 1–11 (2018)

19. Liang, N.Y., Saratchandran, P., Huang, G.B., Sundararajan, N.: Classification of mental tasks from EEG signals using extreme learning machine. International Journal of Neural Systems **16**(01), 29–38 (2006)
20. McGuire, P., Silbersweig, D., Murray, R., David, A., Frackowiak, R., Frith, C.: Functional anatomy of inner speech and auditory verbal imagery. Psychological Medicine **26**(1), 29–38 (1996)
21. Nicolas-Alonso, L.F., Gomez-Gil, J.: Brain computer interfaces, a review. Sensors **12**(2), 1211–1279 (2012)
22. Nieto, N., Ibarrola, F., Peterson, V., Rufiner, H., Spies, R.: Extreme learning machine design for dealing with unrepresentative features. arXiv preprint arXiv:1912.02154 (2019)
23. Nieto, N., Peterson, V., Rufiner, H.L., Kamienkoski, J., Spies, R.: "Thinking out loud": an open-access EEG-based BCI dataset for inner speech recognition. bioRxiv (2021). https://doi.org/10.1101/2021.04.19.440473, https://www.biorxiv.org/content/early/2021/04/20/2021.04.19.440473
24. Pei, X., Barbour, D.L., Leuthardt, E.C., Schalk, G.: Decoding vowels and consonants in spoken and imagined words using electrocorticographic signals in humans. Journal of Neural Engineering **8**(4), 046028 (2011)
25. Price, C.J.: The anatomy of language: contributions from functional neuroimaging. The Journal of Anatomy **197**(3), 335–359 (2000)
26. Suppes, P., Lu, Z.L., Han, B.: Brain wave recognition of words. Proceedings of the National Academy of Sciences **94**(26), 14965–14969 (1997)
27. Tan, P., Sa, W., Yu, L.: Applying extreme learning machine to classification of EEG BCI. In: 2016 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER). pp. 228–232 (2016). https://doi.org/10.1109/CYBER.2016.7574827
28. Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M.: Brain-computer interfaces for communication and control. Clinical Neurophysiology **113**(6), 767–791 (2002)
29. Zhang, Y., Wang, Y., Zhou, G., Jin, J., Wang, B., Wang, X., Cichocki, A.: Multi-kernel extreme learning machine for EEG classification in brain-computer interfaces. Expert Systems with Applications **96**, 302–310 (2018)